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An Artificial Neural Network (ANN) model to predict the electric load profile for an HVAC system ⋆

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Abstract: A better management of the Heating, Ventilating and Air Conditioning (HVAC) systems and the integration of renewable energies are two ways to get a Net Zero Energy Buildings (NZEB). Thus, methods to predict the Electrical Load Demand (ELD) for the HVAC system are extremely important, to reach this goal. This paper describes the development and assessment of a fan-coil power demand predictive Artificial Neural Network (ANN) model for a characteristic laboratory inside a research centre located at Almería (Southeast of Spain). As the model is aimed to be used as part of advanced building energy control schemes, some specific requirements, as a trade off between accuracy and simplicity, have been considered. The main consideration for improving new thermal comfort control system is how to save energy without affect the users' comfort. The performed experiments show a quick prediction with acceptable final results for a short-term prediction horizon using real data. Moreover, a detailed discussion of the obtained ANN model, which has been validated using real data saved from the research centre used as case-study, has been included.

Keywords: Artificial Neural Networks, RBF, HVAC, comfort control.

1. INTRODUCTION

Most people spend more than 90% of their time inside buildings, and almost 50% of the energy consumption is used to obtain a suitable thermal comfort conditions in commercial buildings. Therefore, the development of HVAC systems that do not rely on fossil fuels with a higher energy-efficient is important to reduce energy consumption (Vakiloroaya et al. (2014)). Therefore, the prediction of the Electrical Load Demand (ELD) in the target building or the specific target system in the building is being widely studied nowadays since optimisation energy and balancing with the use of renewable sources through specific control systems requires an accurate knowledge of energy consumption profile in the building (Castilla et al. (2014)).

For buildings located within the European Union (EU), the energy performance should be taking into account at the same time the outdoor climatic conditions and local peculiarities, as well as indoor climate requirements and profitability in terms of cost-effectiveness, as it is pointed out in the guidelines given by the European Commission in the Energy Performance of Buildings Directive (EPBD) (EPBD (2016)).

Artificial Intelligence (AI) methods are a research line that has been experiencing an increasing focus over the past years because of their good fit to this kind of problems. Nowadays AI is used for almost everything, particularly in control system. Among their uses, it is possible to highlight to get and maintain the users' thermal comfort in the buildings. AI includes several techniques as artificial neural networks (ANN), fuzzy logic, support vector machine, genetic programming or a combination of them which is also well-known as hybrid systems (Castilla et al. (2014), Lopez et al. (2004), Singh et al. (2006), Calvino et al. (2004), Castilla et al. (2014), Alamin et al. (2017)).

Many techniques have been applied to the task of electricity demand prediction, such as statistical and artificial

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Fig. 1. Aerial view of the CIESOL building

intelligence methods. There are some cases where system information is only known partially, where some of the physical facts are introduce in the system and the other calculated by AI. This method is called a grey system. In this way, a grey model can be used to analyse the energetic behaviour of the building when only incomplete or uncertain data are available (Rodríguez et al. (2003)).

In this paper models to predict the consumption of the HVAC system used in CIESOL building have been developed. Prediction models based on ANN, which have been chosen for their distinctive features for this problem, have been obtained. Among them, two models have been selected for two seasons, summer and winter.

This paper is organized as follows: in Section 2, CIESOL building is briefly described. In Section 3, the methodology used to develop the model based on neural networks is widely described and an analysis of the energy demand profile of the building used as case study is performed. Section 4 is dedicated to show and discuss the results of the different experiments made. Finally, conclusions and future works are given in Section 5.

2. CIESOL BUILDING

In this paper, a model to predict the consumption of the fan-coil system that is used to maintain the users' thermal comfort conditions inside the rooms of the CIESOL building is presented. The CIESOL building (http://www.ciesol.es) is a solar energy research centre placed on the Campus of the University of Almería in the Southeast of Spain, see Fig. 1.

More specifically, this building is divided into two different floors with a total surface approximately equal to 1072 m^2. In addition, it has been designed to be a Nearly-Zero Energy Building (NZEB) and, thus, it has been designed following several bioclimatic criteria such as the use of photovoltaic panels to produce electricity and an HVAC system based on solar cooling which is composed of a solar collector field, a hot water storage system, a boiler and an absorption machine with its refrigeration tower. Therefore, this HVAC system is able to produce heat or cold air for the whole building as a function of the demanded needs. To do that, heat or cold water flows inside the building and,

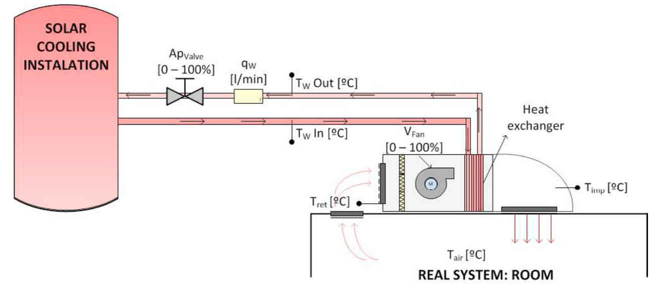

Fig. 2. Scheme of a fan-coil unit

at each room, it goes through a fan-coil unit. This fan-coil unit allows to introduce air at a certain temperature inside each room by regulating both the amount of water which flows through it (by means of a two-way valve), and the volume of air which is introduced in the room (by means of a three-position fan), see Fig. 2. Furthermore, CIESOL building works as a research centre which deals with the study of the implemented bioclimatic strategies, the analysis of their influence over energy efficiency and greenhouse effect gasses reduction, and also, the development of optimization techniques to increase the ratio of renewable energies use against conventional ones. For this reason, it counts with a wide network of sensors and actuators whose measured values are stored in a database by means of a measurement and acquisition software.

3. ARTIFICIAL NEURAL NETWORK MODEL

ANNs mimic the human brain's biological neural network in the problem-solving processes. ANNs can be seen as a black-box that connects the input to the output, with fully connected neurons (nodes), these nodes being connected by weights. They are used for the non-linear mapping between the input data, X, and the output vector, Y, in order to model relations or detect patterns among them. Using supervised training methods, the parameters (weights) and structure can be determined from data.

3.1 Architecture and Methodology

Radial Basis Function (RBF) NN has three type of layers. Firstly, the input buffer which represents the inputs to the network. Second, the hidden layer, which applies a non-linear transformation on the input set, employing typically a large number of neurons, to achieve better results but, at the same time, increasing the complexity of network. Finally, the third layer, which usually has a single neuron, performs a linear combination over the outputs of the neurons from the previous layer. Figure 3 shows a scheme of an RBF NN with one hidden layer.

The output of an RBF ANN can be expressed as:

$$y = \sum_{i=1}^{n} w_i f_i(||c_i - x||_2 \sigma_i) \quad (1)$$

where w_i is the weight associated with the i_{th} hidden layer node, f_i is the radial function, c_i is the location of the centre whereas σ_i is its spread, finally, x is the input point.

The modelling capabilities of this network are determined by the shape of the radial function, the number and

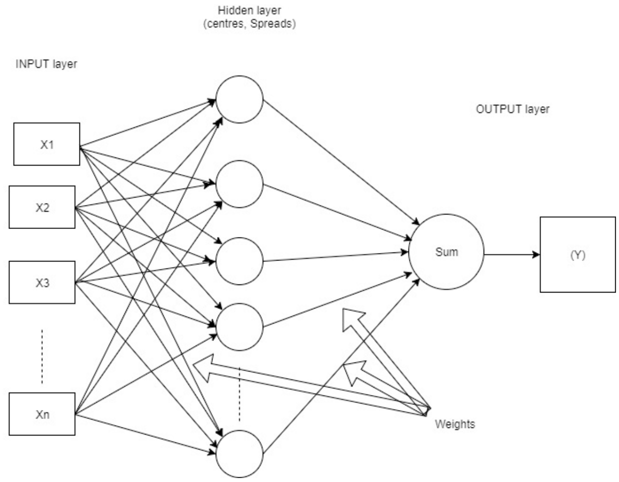

Fig. 3. RBF ANN scheme

placement of the centres, and the width (spread) of the function. Functions as radial linear function, radial cubic function, Gaussian function, thin plate spline function, multi-quadratic function, inverse multi-quadratic function or shifted logarithm function can be selected to be the radial function for the RBF NN. However, the Gaussian one, as shown in Eq. 2 is the most used function.

$$f_i(x) = e^{\left(-\frac{\|c_i - x\|_2^2}{2\sigma_i^2}\right)} \tag{2}$$

In general, RBF training is performed using a gradient-based algorithm, which minimizes the training error. The training process can be terminated when the minimum of the generalization error (the error obtained in an unseen -generalization- dataset, as training evolves) is obtained. This scheme is a way to solve the problem known as over-fitting. To compare different trained models, with possible different model structure, a third dataset, denoted as a testing dataset, is needed. Hence, three different sets of data are used: i) training, ii) generalization and, iii) testing data sets (Ferreira and Ruano (2000), Haykin (2005)).

3.2 The data construction

A set of historical data from the CIESOL building has been collected. Specifically, the historic dataset comprises of one year since the 1^{st} of April 2013 to 31^{st} of March 2014. This dataset is used to obtain the RBF ANN proposed in this paper. It is composed of 365 days, with a sample time of 1 minute which accounts for a total of 525600 samples. To obtain a more accurate model, all weekend samples are removed from the dataset, since there is nobody in the room, implying that the HVAC will be off all the time. Besides that, the original dataset is split in two datasets: one for the summer season and another for the winter one, which will have different properties. For summer, the months of June, July, and September have been considered, August is a holiday period in Spain, thus, it has not be taken into account. In a similar way, for winter, the months of December, January, and February have been considered.

A summary of the variables that are measured by the sensors network of the building and how they are used in the NN is shown in table 1. An NARX scheme is used, which means that in addition to the exogeneous inputs. two delayed values of the output (the fan-coil energy) are used as NN inputs. The exogenous inputs are the impulse air velocity, delayed by one sample and the current value of the inside air temperature.

Table 1. Input and Output Data used for the NN

Sample	Data	units	I/O
$E_{fan}(t)$	Energy consumption of the fan-coil	W	Output
$E_{fan}(t-1)$	Energy consumption of the fan-coil (one sample delay)	W	Input
$E_{fan}(t-2)$	Energy consumption of the fan-coil (two sample delay)	W	Input
$Anemo_{fan}(t-1)$	Impulse air velocity (one sample delay)	m/s	Input
Ti (t)	Indoor air temperature	° C	Input

Due to the sample time of the historic data, the power consumption signal has a random white noise. Therefore, to remove this noise a smooth filter has been used. More specifically, the MATLAB *smooth* function has been applied to the data. This function smooths data using a 5-point moving average, that is, the moving average filter smooths data by replacing each data point with the average of the neighbouring data points defined within the span. This process is equivalent to a low pass filter, and is applied to the inside temperature as well. Hence, the response of the smooth function is given by the following difference equation:

$$\begin{aligned} y_s(i) = \frac{1}{2N+1}(y(i+N) + y(i+N-1) + ... \\ .. + y(i-N)) \end{aligned} \tag{3}$$

where $y_s(i)$ is the smoothed value for the i_{th} data point, N is the number of neighbouring data points on either side of $y_s(i)$, and $2N+1$ is the span (MathWorks (2017)).

Nevertheless, each one of the two datasets, summer and winter, are split into subsets after removing all the samples that are measured incorrectly or not measured. Finally, the summer dataset contains 89400 samples, and the winter one is composed of 93600 samples, After that, both datasets are divided divide into a training subset with 36% of the total samples, a generalization subset of 24%, and a testing subset of 40%.

3.3 The experiments

Predictions of the power demand of a representative laboratory (room) of the CIESOL building have been obtained through the ANNs models, each of them with different configurations. At this point, it is necessary to determine which of the obtained ANNs is the best ones. For this aim, the Normalized Root Mean Square Error (NRMSE) has been used. This index is the percentage of the Root Mean Square Error (RMSE), for the prediction horizon of one step. The experiments had been run for each data subsets separately, for all the combinations of these parameters: i) the number of the centres can be 3, 6, 9, 12 and 15 and, ii) the λ parameter can be 0.05, 0.01, 0.005 and 0.001. This parameter is the termination criterion with early stopping,

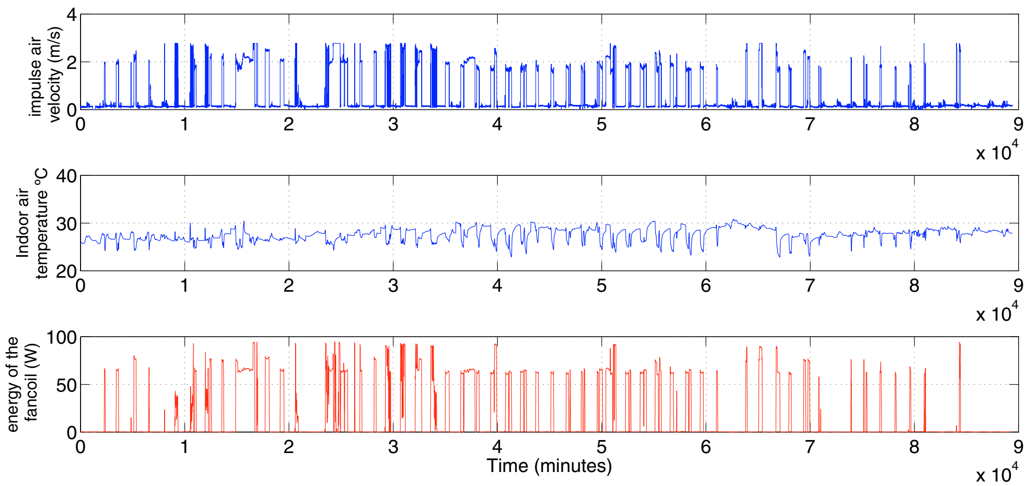

Fig. 4. The input and output signals that are used in NN

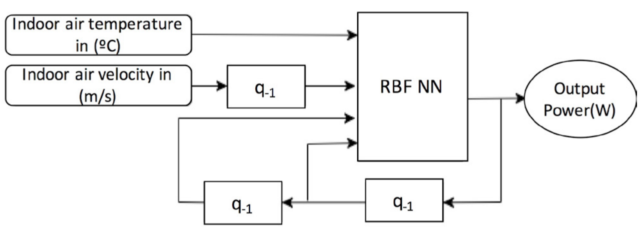

Fig. 5. Structure of the ANN proposed in this paper

since an early stopping method with generalization dataset has been used, it is normally interrupted the training when the resolution parameter specified is achieved before the iteration met, for better understanding and more details see Ruano et al. (2005).

The structure of the proposed ANN in this paper to predict the power demand of the fan-coil in one room of the CIESOL building is shown in Fig. 5. The RBF ANN in this work, used to predict the power consumption by fan-coil has been trained using the Levenberg-Marquardt (LM) algorithm (Olofsson et al. (1998), Marquardt (1963)) which minimizes a modified training criterion (Ruano et al. (1991), Ferreira and Ruano (2000)). This method has been previously used with success in Alamin et al. (2016), and Ferreira et al. (2012).

4. RESULTS AND DISCUSSION

From the training of the ANN with real data from the bioclimatic building, different models have been obtained. A summary is shown in table 2 for the best five summer models, whereas in table 3 the best five winter models are summarised. As it has been pointed out before, the NRMSE index has been used to assess the performance on the different models. Moreover, validation results for one step ahead (using 1-minute interval) show an appropriate performance with an NRMSE less than 0.85% for the worst case. Specifically, the best model for summer is the first one as it is the less complex NN structure with the best accuracy. On the other hand, for the winter case the best model has 0.52% in the worst case. As in the previous case

Table 2. Results of the best five obtained models for summer

Model No.	No. of centres	NRMSE training	NRMSE gen.	NRMSE testing
1	9	0.0083	0.0080	0.0083
2	12	0.0083	0.0080	0.0083
3	12	0.0083	0.0080	0.0083
4	9	0.0084	0.0081	0.0084
5	9	0.0083	0.0080	0.0084

Table 3. Results of the best five obtained models for winter

Model No.	No. of centres	NRMSE training	NRMSE gen.	NRMSE testing
1	6	0.0059	0.0066	0.0051
2	12	0.0059	0.0066	0.0051
3	6	0.006	0.0065	0.0051
4	6	0.006	0.0065	0.0051
5	12	0.0059	0.0066	0.0052

the best model is the first one, as well it has the smallest complexity achieving the best accuracy.

The prediction of the power demand for one step ahead for the five obtained models for summer and winter cases, for a specified period of time, can be seen in Figs. 6 and 7 respectively. Figure 8 shows the prediction of power demand for the fan-coil for the best model, the model 1, for 1, 5, 10 and 15 steps ahead. In Fig. 9, it is possible to see the same results for model 1 of the winter period. As the reader can see in both figures the performance of the models decrease when the number of steps ahead predictions increases.

Table 4 shows some statistics for the best five obtained models for summer using, besides that the NRMSE index, these indicators: Mean Absolute Error (MAE), Mean Relative Error (MRE), Maximum Absolute Error (MaxAE), Standard Deviation Error (StDE) and Normalized Mean Absolute Error (NMAE) for summer. On the other hand, table 5 shows the same statistics for the winter case.

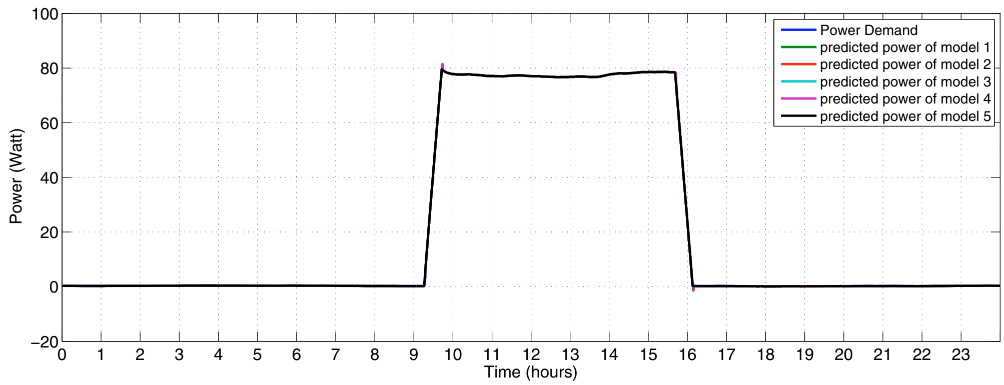

Fig. 6. Power demand prediction for one step ahead of the five obtained models for summer

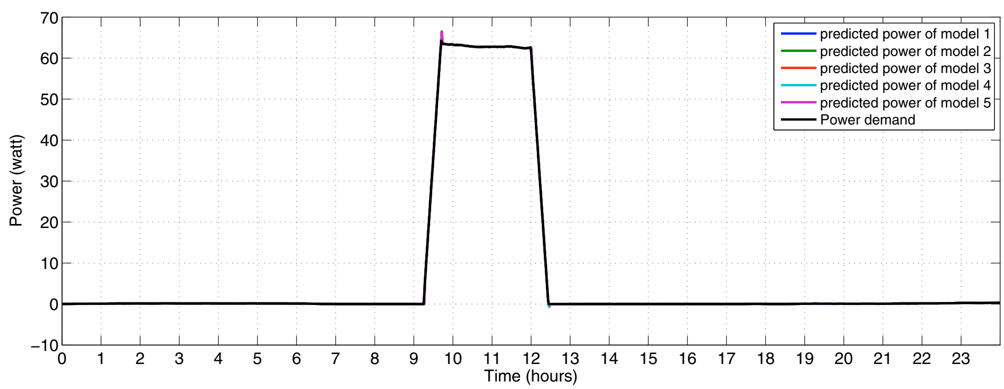

Fig. 7. Power demand prediction for one step ahead of the 5 obtained models for winter

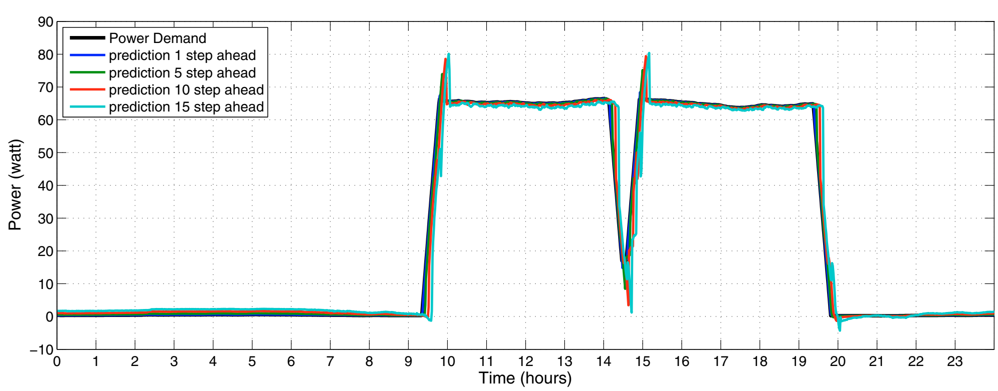

Fig. 8. Model 1, 15 steps ahead power demand prediction for summer

Table 4. Statistical analysis of the best five obtained models for summer

No.	steps ahead	NRMSE	MAE	MRE	MaxAE	StDE	NMAE
1	1st	0.0099	0.0579	0.3450	7.0046	0.2209	0.0073
	15th	0.2975	3.7176	46.8871	86.0279	6.4472	0.4687
2	1st	0.0096	0.0450	0.2199	7.2965	0.2151	0.0057
	15th	0.2098	2.1173	16.3099	80.5860	4.6304	0.2669
3	1st	0.0097	0.0471	0.1707	7.2523	0.2166	0.0059
	15th	0.2607	2.9095	23.9566	83.4681	5.7338	0.3668
4	1st	0.0098	0.0522	0.3141	7.3882	0.2191	0.0066
	15th	0.2359	3.0900	40.1141	85.7121	5.2633	0.3895
5	1st	0.0097	0.0464	0.2462	7.4104	0.2172	0.0058
	15th	0.2058	1.5047	10.2133	88.6098	4.5983	0.1897

Table 5. Statistical analysis of the best five obtained models for summer

No.	steps ahead	NRMSE	MAE	MRE	MaxAE	StDE	NMAE
1	1st	0.0060	0.0076	0.9646	3.4487	0.0579	0.0045
	15th	0.1851	0.3542	33.7254	53.1640	1.7972	0.2063
2	1st	0.0059	0.0068	0.8256	3.5127	0.0577	0.0040
	15th	0.1752	0.3697	43.2360	54.3131	1.7012	0.2153
3	1st	0.0059	0.0076	1.0201	3.5141	0.0577	0.0044
	15th	0.1765	0.3498	36.1000	53.4357	1.7134	0.2037
4	1st	0.0060	0.0071	0.9021	3.5248	0.0578	0.0041
	15th	0.1794	0.3138	30.3301	54.5998	1.7420	0.1827
5	1st	0.0060	0.0072	0.4660	3.5251	0.0586	0.0042
	15th	0.1784	0.2322	8.9919	54.6921	1.7319	0.1352

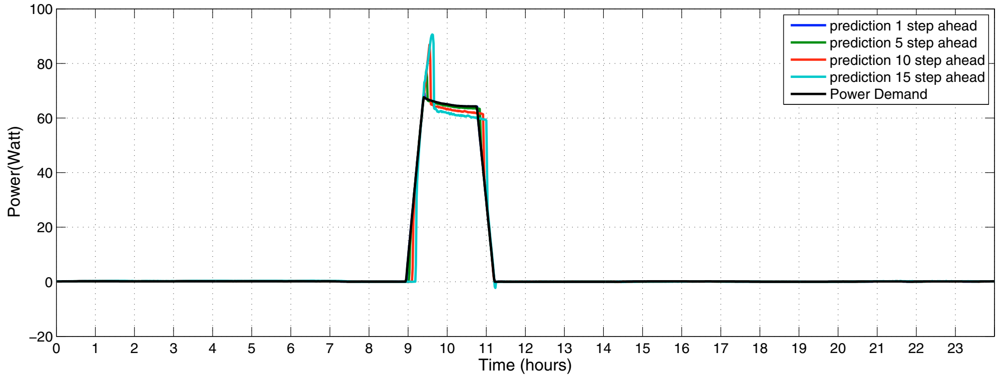

Fig. 9. Model 1, 15 steps ahead power demand prediction for winter

5. CONCLUSION AND FUTURE WORKS

This paper deals with the development of an RBF ANN to predict the energy consumption of a fan-coil system. The obtained RBF ANN shows optimistic results with a simple structure as the best method for the prediction of the electric load for an HVCA system. The fact that the developed RBF ANN model is very simple and the computational resources for its application are tiny and easily available at modern automation systems, gives to the model its advantage to be used in several fields. In particular, in order to apply it to a control system, only data from simple sensors and electric power measurements are required.

A future research line is the use of the ANN as the basis of a control system which, through the ANN model, will be able to maintain the thermal comfort of the users of building whereas the energy consumption necessary to reach this thermal comfort situation is minimized. Following this research line, another ANN will be developed in order to predict the number of users (people inside the room), that can used as input for Model-based Predictive Control (MPC). A deep learning structure will also be considered and compared with the ANN alternative.

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